Climate Variability and Diarrheal Diseases: Evidence from Outpatient Data from Uganda[1]

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Abstract

SDGs 3 and 13 are dedicated to health and climate change, respectively. The relationship between the two is gaining increasing importance, albeit scanty empirical research about the same. We apply econometric techniques on outpatient and climate data to investigate the effect of climate variability on the incidence of diarrheal diseases in Uganda. Regression results indicate a strong negative association between rainfall and diarrheal diseases, with these cases significantly higher when monthly rainfall is 20% below the month-specific 87-year average. The results imply the need to incorporate climate change into healthcare planning to ensure readiness to contain disease outbreaks related to climate shocks.

1. Introduction

Climate change is a major global issue, defined as significant changes in average and peak temperatures, humidity, atmospheric pressure, precipitations, wind patterns and water salinity and decreases in mountain and polar glaciers (McMichael, 2013). This global threat is already manifesting in various forms including, but not limited to global rise in average and peak surface temperatures, increased frequency of heat waves, cyclones, droughts, floods and other extreme weather events as well as the altered distribution of allergens and vector-borne diseases (Massimo Franchini & Pier Mannuccio Mannucci, 2015). Global temperatures increased by 0.7^{0}C over the past 50 years and are expected to rise by 1.8-4^{0}C by the year 2100 (IPCC, 2014; Hansen et al., 2006). One single most important cause of global warming is greenhouse gas emissions from fossil fuel-based power generation, transport, agriculture and mining sectors that increase the heat-retaining capacity of the lower atmosphere (Anthony J. McMichael, 2013). It is intriguing that the developing world – especially Africa – will be hit

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earliest and the worst (Collier et al, 2008) despite the continent being the least contributor to the anthropogenic emissions that have led to global warming.

The continent's relative vulnerability to climate change partly stems from extreme poverty and the reliance on rain-fed agricultural systems that are vulnerable to frequent natural disasters such as droughts and floods (IPCC 2001). The same report clearly states that in some parts of Asia and Africa, an upward trend in the frequency and intensity of droughts has been observed in recent decades. As a result, undernutrition and malnutrition, increased rates of infectious diseases, cases of instability, mass population movements are more likely to be observed. This means that, human health, political stability and economic development of the African countries will be compromised by the devastating consequences of climate change.

There is an existing body of literature that associates climate change with adverse effects on various sectors, ranging from Agriculture, Energy, Transport, and Economy. The first strand of literature associating climate change impacts on the Agriculture sector demonstrates that sufficient food production and access to safe water are threatened by desertification and droughts (Parry et al., 2004; Hanjra and Qureshi, 2010; Wheeler and Von Braun, 2013). In many agrarian economies, the impact of changing agricultural seasons and intensified extreme weather events is already causing tremendous declines in crop yields due to crop failure and crop loss (Ringler et al., 2011). The ultimate impact on households is a substantial reduction in food security, especially female-headed households whose access to coping mechanisms and resources is largely constrained (Akampumuza and Matsuda, 2016; Asfaw and Maggio, 2017). In the Energy sector, although climate change is likely to reduce demand for heating energy in the temperate world, electricity consumption is likely to increase to match the increased demand for cooling energy especially in the tropical world (Karl, 2009). Hydropower production might be at risk in regions vulnerable to changing precipitation patterns while sea level rise might affect energy production and distribution systems in other regions (Karl, 2009). Threats to the Transport sector include storm surges, sea level rise, and extreme weather events which are likely to cause major damages to transportation systems (Stern, 2007; Mills & Andrey, 2002).

The Health sector is among the vulnerable sectors that have been under researched in relation with the potential impacts of climate change. The first IPCC report released in 1990 featured no chapter on health, a pattern that has been observed in many of the subsequent reports and research. Even then, the existing research on climate change and health have largely concentrated on advanced economies of Europe and North America (Verner et al., 2016). In low-income countries particularly, the scanty research on the health impacts climate change is partly attributable to data unavailability. We contribute to this knowledge gap by analyzing the impact of extreme rainfall and temperature on the incidence of diarrheal diseases in Uganda using outpatient diagnosis records. The rest of the paper is organized as follows: Section 2 reviews the existing literature on the relationship between climate change and human health, detailing the mechanism of this relationship in different geographical regions. Sections 3 and 4 respectively elaborate the data sources and estimation strategy used in this paper. The empirical results are presented in Section 5 while Section 6 concludes the paper and provides policy recommendations.

2. Global policy and research attention towards climate change and health

In September 2000, the UN General assembly adopted the eight Millennium Development Goals (MDGs) of which three were directly related to health while health – Gola 1: eradicate extreme poverty and hunger; Goal 4: reduce child mortality; Goal 5: improve maternal health; Goal 6: combat HIV/AIDS, malaria and other diseases. Health was also implicitly embedded in almost all of the other MDGS. For example, Goal 7: ensure environmental sustainability, has implications for the sustainability of healthcare systems amidst climate change and variability while Goal 8: develop a global partnership for development, implies medical and global health collaboration in the fight against major diseases. A lot was achieved regarding the MDGs especially in the health sector, although implementation in some developing countries was plagued by numerous challenges and performance was not remarkable. Again in September 2015, the UN General Assembly adopted the post-2015 agenda "Transforming our world: the 2030 agenda for sustainable development." This agenda has 17 goals and 169 targets and are applicable to both low and middle income countries. One specific goal – SDG 3 – and the associated 13 targets are focused on health. SDG 13 – "Take urgent action to combat climate change and its impacts" – is also a major focus due to its effects on all sectors of economic development including the health sector. A characteristic feature of these SDGs is their interlinkage, not only with themselves, but also with population health. It is therefore imperative to increase efforts and resource allocations towards the SDGs 3 and 13 in order to eradicate poverty, hunger and vulnerability as a pathway to sustainable development. Knowledge generation through research and the incorporation of climate information in disease surveillance systems is handy to this cause.

Research plays a key role of informing health policy with the outbreak and spread patterns of diseases attributable to climate change and climate variability, along with recommendations on potential strategies to minimize adverse effects. Climatologists, scientists and public health experts have for many years observed and mapped the geographical incidence of infectious diseases in relation to weather and climate. In the recent past, it is projected that in the coming decades there will be increases in both vector-borne and diarrheal disease. Because there are many factors that influence the above diseases, it is still difficult to explicitly attribute the increased incidences of these diseases to global climate change. However, a lot of work has been published showing correlation between climate variability and increased incidences of diseases like diarrhea, cholera, malaria, Lyme disease among others.

There are mixed views in the existing literature regarding the potential and observed impacts of climate change on public health. On the one hand, some scholars have demonstrated a possible positive impact in mid-latitudes, particularly in the form of reduced pneumonia, bronchitis and arthritis (Massimo Franchini & Pier Mannuccio Mannucci, 2015). This claim is based on the possibility that warmer temperatures are likely to reduce the spread of diseases related to cold weather. On the other hand, another body of literature reveals that the potential positive impacts are unlikely to match the negative impacts of climate change on human health, particularly longer hot days with adverse health consequences (Meehl Tebaldi, 2004). This is based on the higher risk of typhus, cholera, malaria, dengue fever, West Nile virus infection and other climate-related diseases, posing great danger to human wellbeing and health (McMichael & Lindgren, 2011).

Extreme temperature events have been linked to acute coronary syndromes and myocardial infarction (Dilaveris et al., 2006; Goerre et al., 2007), heat-related illnesses and deaths among children and the elderly in North Amercia and Europe (Medina-Ramon et al., 2006), hospital visits related to *argina pectoris* (Abrignani et al., 2009) and asthma in the United States (Lin et al., 2009). Hospital admissions due to respiratory diseases have been found to associate with heat waves resulting from high surface temperatures (Anderson et al., 2013) and smoke exposure resulting from heat-induced wild fires (Lim et al., 2012). Ozone exposure that results from the increase concentration of carbon dioxide and higher surface temperatures is claimed to cause human respiratory problems (Bell et al., 2007) and hospital admissions related to cardiovascular diseases (Simpson et al., 2005).

Climate change is also anticipated to alter the reproduction and spread of some climate-sensitive disease vectors and stimulate the spread of vector-borne and other infectious diseases. The risk of diarrhea – especially among children – is expected to increase due to reduced availability of safe water following droughts and El Nino events (Khasnis and Nettleman, 2005). It is estimated that an increase in surface temperature by 1^0C leads to increased risk of diarrheal infections by between 3% and 11% (Mannussio et al., 2015). El Nino events have also been reported to result in dengue fever outbreaks in the Asia-Pacific region (Hales et al., 1996). The expansion of vectors into areas previously inhospitable due to unfavorable temperature and humidity has given way to outbreaks of vector borne diseases. Warmer temperatures have resulted in increased incidences of West Nile infection in the Mediterranean area and North Africa (Grazzini et al., 2008) and malaria in some African highlands, particularly in Kenya (Zhou et al., 2004). Other health impacts of climate change include malnutrition due to reduced crop yields (Sellman and Hamilton, 2007) and increased household out-of-pocket expenditure related to particular infectious diseases (Lohmann & Letchenfield, 2015).

Diarrhea disease is the leading cause of death in children under 5years old, claiming the lives of around 525,000 children annually. A bigger proportion of these children is from the developing countries whose adaptive capacity is still limited. It is estimated that between 2030 and 2050, 250,000 more deaths per year will occur due to malnutrition, diarrhea and heat stress. It is also expected that climate impacts could increase the burden of diarrhea by up to 10% by 2030 in some regions (WHO, 2003). Existing evidence on the effect of climate change on diarrhea is however inconclusive; conflicting relationships have been reported, often depending on the geographical region covered by the research. While some literature points to increased cases of diarrhea during periods of flooding (Wade et al, 2004; Waring et al 2005; Woodruff et al, 1990), other researchers found more diarrhea cases during dry periods (Alexander et al, 2013; Lloyd et al, 2007). The data used ranges from self-reported disease records, hospital records and outbreak reports. Short-term impacts on diarrhea due to high and low rainfall (Curriero et al., 2001; Singh et al., 2001). As rainfall increases, the diarrhea pathogen is diluted, and hence the incidence of diarrhea are likely to reduce, at least in the short term (Singh et al., 2001).

To the best of our knowledge, no detailed empirical examination has been done in relation to the association between climate change and health in the context of Uganda. One empirical assessment that focused on diarrhea in 13 Sub-Saharan African countries did not draw down on the region-specific challenges (Bandyopadhyay et al., 2012). Besides, the study relied on self-reported illnesses from household surveys, which could be prone to recall bias. Our study aims to contribute to this under researched topic by quantifying the relationship between extreme rainfall and temperature events on the one hand and the incidence of diarrheal diseases on the other, in the context of one of the most vulnerable sub-regions of Uganda. There are three clinical types of diarrhea: acute watery diarrhea – lasts several hours or days, and includes cholera; acute bloody diarrhea – also called dysentery; and persistent diarrhea – lasts 14 days or longer. In this paper, we analyze the first two types for which data are available.

We contribute to the existing literature in two ways; first, by focusing on a country in Sub-Saharan Africa, one of the most under-researched regions in relation to this topic. We particularly focus on Uganda, a country that has barely implemented any projects to adapt the health sector to climate change. The 2015 WHO/UNFCC Climate and Health Country Profile for Uganda indicates that the country has not initiated actions to build institutional and technical capacities to work on climate change. Likewise, a national assessment on the health impacts of climate change is largely inexistent in the country. The healthcare budgeting processes have not allocated sufficient funds to strengthen the resilience of the health infrastructure, neither has climate information been incorporated in the Integrated Disease Surveillance and Response (IDSR) system. We therefore anticipate that our results will be a first step to creating awareness about the potential health impacts of climate change and the need to incorporate them in healthcare planning. As a second novelty of our study, we use outpatient diagnosis rather than self-reported illnesses from household surveys. By utilizing positive diagnoses as indicators of disease occurrence and incidence, we alleviate potential recall bias to which self-reported illnesses are prone.

3. Data and summary statistics

The analysis in this paper draws on three major data sources. First, between August and September 2016, we collected data on the prevalence of infectious diseases from outpatient records provided by District Health Offices in the in the Teso Sub-region of Uganda. Out of the eight districts that constitute the sub-region, three districts – Kumi, Bukedea and Kaberamaido were visited and data on the total number of outpatient visits was obtained. Specifically, we obtained information on the number of monthly new hospital attendances and re-attendances and the number of positive diagnoses for diarrhea and dysentery. We were also able to obtain these data disaggregated by gender and age composition of the patients which we use to assess the relative vulnerability of the respective demographic categories. Where data were available, we obtained outpatient records spanning a period of six years between 2006 and 2011, albeit some missing data in some months and years.

We present the summary statistics of the monthly hospital records stratified by age and gender in Table 1 and by record year in Table 2. In Table 1, the number of new attendances and re-attendances as well as the cases of diarrhea and dysentery is disaggregated by the demographic composition – age and gender of the patients. At both age groups, more females tend to visit hospitals than their male counterparts, with the number of new female attendees aged five years and above doubling that of male attendees in the same age category. A similar observation holds for the number of re-attendances and the cases of diarrhea and dysentery.

The second data source is climate data from the District Environmental Offices and the East African Civil Aviation Academy which collects detailed climate information for the whole of the Teso Sub-region. We obtained monthly rainfall averages covering a period of 87 years, long enough to enable the computation of month-specific longer-run averages from which deviations are calculated and each month's rainfall then categorized as either insufficient or in excess of the month-specific long-term average. We return to this detailed categorization in the methodology section that follows shortly. Minimum, maximum and average temperatures were also obtained but available records only covered the period 2005-2015 and hence, we restrict these variables to the analysis period 2006-2011. As reported in Table 3, mean monthly rainfall for the sub-region across the analysis period was 115 millimeters with minimum and maximum averages being 3.6 and 310.8 millimeters, respectively. The mean monthly temperature for the same period was 25 degrees Celsius, with hottest months reaching as high as 34 degrees Celsius. Compared to a national average of 22.5^{o}C, these are relatively high figures, reflecting the dry and hot climate of the sub-region.

As a third source of data, we use the Uganda National Household Survey (2006) and its panel extension – the Uganda National Panel Survey covering the years 2010 to 2012. The key household-level and village-level variables of interest to this study are aggregated to the district level to obtain district-level characteristics that are deemed important in the analysis of incidences of diarrhea and dysentery as reported in Table 3. On average, 49% of the households in the sub-region have no access to a toilet. The lack of access to toilet facilities implies open defecation as an alternative, posing a high risk of diarrheal diseases. The diarrhea risk is exacerbated by the fact that 87% of the sub-region's households have no access to handwashing facilities at their toilets and that less than one third of the sample households have no access to safe drinking water. With regards to physical access to health services, an average household travels 26 kilometers to access the nearest government hospital.

4. Methodology

We presume a linear relationship between extreme climate the variables and the number of outpatient visits using the model below, which we estimate using ordinary least squares (OLS).

$$OPD_{ijt} = \alpha + RainDev_{jt} + Temp_{jt} + Demog_{ijt} + DistChat_{it} + \varepsilon_{ijt} \qquad (1)$$

Where OPD represents the monthly number of outpatient visits recorded by district *i* in month *j* of year *t*. The first measure of hospital visits takes into account new attendances, which basically corresponds to cases where the patient visits the health facility for the first time. On the other hand, re-attendances refer to recurring visits by existing patients. For both new attendances and attendances as measures of monthly hospital visits, the number of visits is an aggregated measure of all hospital visits for each of the corresponding months, irrespective of the reason or disease for which the visit was made. Whereas these two measures provide a basic understanding of the nature and trend of hospital visits, they do not allow for a detailed assessment of the disease-specific patterns. This is quite important, especially given that different diseases could react differently to different weather patterns and seasons. In order to better understand the association between rainfall and temperature patterns on the one hand and the incidence of diarrhea and dysentery, we use, as the number of monthly hospital visits for which diagnosis results were positive for each of the two diseases.

We control for two main climate variables – rainfall and temperature. The rainfall variable is represented by $RainDev$ which is a binary indicator taking the value one if rainfall for month j is "abnormal". More specifically, the rainfall total received by the sub-region in a particular month is classified as "abnormal" if it was 20% higher or lower than the long-run average for the respective months. Long-run in the sense of this paper refers to the 87-year average spanning from 1921 to 2011. This period is presumably long enough to capture long-term shifts in rainfall patterns and totals, consistent with the definition of climate change. Based on this classification criterion, two dummy versions of the "abnormal rainfall" variable are used separately: excess rainfall refers to cases where total rainfall for the month was 20% higher than long-term (1921-2015) average and insufficient rainfall if it was 20% lower than long-term average.

$Temp$ is mean monthly temperature (degrees Celsius) for the sub-region. Unlike the case of rainfall variables, available temperature data for the sub-region could not permit calculation of monthly deviation from long-term averages. $DistChat$ represents district-level characteristics that we presume ex-ante to influence the incidence of diarrhea and dysentery. The particular variables controlled for include the proportion of households with access to safe drinking water, proportion of households without toilet and hand washing facilities at the toilet, average distance to the nearest government hospital and the proportion of children below age six. The error terms which is assumed to be independently and identically distributed (i.i.d) is represented by ε.

The above OLS results give a rough picture about the response of diarrheal diseases to climate variability. However, as a major limitation of linear models, they fail to account for the limited number of possible outcomes of the response variable and as such, they are not appropriate for modelling count data. In order to overcome this limitation, we apply a Poisson regression model which estimates the number of new attendances, re-attendances, diarrhea and dysentery cases in a given month. The Poisson model requires that the outcome variable be count in nature, counting the number of occurrences in a given exposure space – typically time or a unit area. This fits well with our outcome variables observed in a given month. The functional form of the underlying Poisson model is selected under the simplifying assumption that it produces non-negative values, which is the case with our disease incidences. The outcome variable (y_i) is assumed to follow a Poisson distribution and its mean (λ_i) conditional on the covariates (x_i) is given as;

$$E\{y_i \mid x_i\} = \lambda_i = e^{x_i'\beta} \tag{2}$$

Where e is the base of the natural logarithm and y_i is denotes separate outcomes as the number of new outpatient attendances, re-attendances, diarrhea and dysentery cases. All covariates are represented by the vector x and their corresponding coefficients are represented by parameter vector β. The same covariates used in the previously presented OLS model are used in the Poisson model. The probability mass function for each value of possible value of the outcome variable is given as;

$$P(y_i = y \mid x_i) = \frac{e^{-\lambda_i}\lambda_i^y}{y!} \; where \; y = 0,1,2, \ldots and \; y! \; is \; the \; factorial \; of \; y.$$

The log likelihood function underlying the maximum likelihood estimation process is then specified as;

$$\log L(\beta) = \log\left\{\sum_{i=1}^{N} \frac{e^{-\left(e^{x'\beta}\right)} e^{\left(x'\beta\right)^y}}{y!}\right\} \tag{3}$$

After algebraic manipulation, the log likelihood is given as the sum of the log probabilities;

$$\log L(\beta) = \sum_{i=1}^{N}\left\{-\left(e^{x'\beta}\right) + y(x_i'\beta) - \log y!\right\} \tag{4}$$

5. Econometric results

In Table 4, we present the results from the OLS estimation of equation (1). Columns 1 and 2 reveal an increase of 656 and 199 cases of outpatient new attendances and re-attendances, respectively, when monthly rainfall is 20% lower than the month-specific long-term average. These estimates however make limited intuition, as these two measures of hospital visits are rather general and do not give insights into the nature of the disease for which the hospital visit was made. The subsequent columns breakdown the reason for the patient visit, revealing the number of positive cases diagnosed for two infectious diseases – diarrhea and dysentery. The strongest association exists between the insufficient rainfall dummy and the number of diarrhea cases. Months with rainfall totals 20% lower than the long-tern month-specific average are associated with 20 more cases of diarrhea and two more cases of dysentery while holding other covariates constant. Evaluated at the mean diarrhea cases during months of normal rainfall, this translates into a 13.6% increase in monthly diarrhea cases and 10.6% increase in dysentery cases, holding other covariates constant. This finding is in line with Lloyd et al. (2007) who found a 4% increase in diarrhea incidence as rainfall decreases by 10 millimeters. We presume that the mechanism of this effect is the reduced availability of safe water during dry months which forces households to resort to unprotected water sources and reduce hygiene practices including hand washing. This presumption is corroborated by Bandyopadhayay et al. (2012) who found a negative association between rainfall and diarrhea cases in 13 African countries, attributing the association to reduced availability of safe water for drinking and home use during exceptionally dry months. We also validated the presumption through focus group discussions conducted in the study area during the data collection period. We do not find any systematic relationship between minimum and maximum temperature variables and the incidence of the diseases studied except dysentery which increases by 1.7 cases for every degree Celsius of maximum temperature. Given the high negative correlation (correlation coefficient = -0.5586) between rainfall and temperature, the temperature effect could perhaps be overcrowded by the rainfall effect.

We further find a strong positive relationship between the district-level proportion of households without access to a toilet and outpatient new attendances, re-attendances and the cases of diarrhea. Specifically, a percentage point increase in the proportion of households without toilet corresponds to an increase in diarrhea by 11 cases. The lack of toilet facilities implies unsafe stool disposal which increases the risk of diarrhea (Cairncross and Yonli (2000; Curtis and Cairncross, 2003). The number of outpatient visits is also found to increase with the average distance in kilometers between an average household and the nearest hospital. For every kilometer away from the hospital, new attendances, re-attendances and diarrhea cases increase by 38, 173 and 8, respectively. This finding is perhaps indicative of the difficulty in accessing healthcare services in some communities which could translate into reduced frequency of healthcare visits as well as inaccessibility of healthcare and hygiene information.

We present the Poisson regression results in Table 5. The coefficients reported are incident rate rations, indicating marginal changes in the number of disease cases responding to a one unit change in the each of the independent variables. By construction, the coefficients of the Poisson regression model are the differences in the logs of expected outcomes given a one unit change in the respective covariates. Incident rate rations reported in Columns 1 through 4 indicate that the number of new attendances, re-attendances, diarrhea and dysentery cases is 12.2%, 8.9%, 12.8% and 11.3% higher in months when rainfall was 20% below the long-term average. All other covariates are qualitatively similar to the OLS results. The corresponding OLS estimates for new attendances, re-attendances, diarrhea and dysentery evaluated at the mean of normal months are 13.5%, 8.7%, 13.6% and 10.6%, respectively. One limitation of the standard Poisson regression is however that it assumes equality of the mean and its variance. However, checks revealed that this assumption is implausible with our data. We therefore estimate the regressions using a generalized version, that is, the Negative Binomial Regression Model (NBRM), relaxing the equality assumption. Like in the case of Poison distribution, the mean is denoted by mu but in addition, the NBRM allows for a deviation of the variance from its mean. The variance under the NBRM model is given by $\mu(1+\alpha\mu)$, clearly indicating the Poisson distribution can only be tenable if α tends to zero. As indicated by a significant *alpha* in Table 6, the significant alpha coefficient indicates over dispersion, that is, a variance greater than its mean, which would potentially confound the standard Poisson regression results. The NBRM results are closer, in magnitude and significance, to the standard Poisson results, except for dysentery.

6. Conclusion and discussion.

SDGs 3 and 13 are dedicated to health and climate change, respectively. The relationship between the two is gaining increasing research importance, albeit scanty empirical research about the same. The research gap is even more pronounced in developing countries, partly due to data unavailability. We apply econometric techniques on outpatient and climate data to investigate the effect of extreme rainfall and temperature on the incidence of diarrhea and dysentery in Uganda. The key novelty of our approach is the use of mobile phone technology to ameliorate the data limitation idiosyncratic of many developing countries. Given the unavailability of soft copy records on disease incidence in the study districts, we took over 5,000 photos of hard copy archives of outpatient records from district health offices, which we digitized to constitute our database. The associated benefit is the use of actual disease diagnosis rather than self-reported illnesses from household surveys as is the case with most empirical studies on the topic. Our approach hence ameliorates potential recall bias in reporting exposure to diarrheal cases. Regression results indicate that outpatient visits related to acute diarrhea and dysentery tend to increase during months when rainfall figures are 20% lower than the month-specific 87-year average.

We presume that the pathway to the observed effect is the reduced availability of safe drinking water during extremely dry months which forces residents to resort to unprotected springs and ponds as alternative sources. Our presumption was corroborated by focus group discussions conducted in the study area during the data collection period. The results carry key policy implications; first, by directing policy attention to promoting access to clean water and sanitation facilities directly linked in order to lower the incidence of diarrheal diseases. Secondly, since a large proportion of Ugandans are not covered by private and public health insurance schemes, exposure to climate-related health shocks is likely to increase their out-out-pocket health expenditures. This would necessitate reinvigorating health care financing to reduce the financial burden in terms of out-of-pocket expenditures to which households and individuals are exposed. Finally, the results carry a policy message regarding the need to include climate information in the Integrated Disease Surveillance and Response (IDRS) aimed to increase the sustainability and resilience of healthcare systems amidst climate change and variability.

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Table 1: Monthly number of hospital visits by age and gender categories

	Male Age 0-4		Female Age 0-4		Male Age 5+		Female Age 5+	
VARIABLES	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)	Mean (7)	SD (8)
Number of new hospital visits	3,492	2,050	3,830	2,165	4,153	2,205	8,710	5,979
Number of hospital re-visits	1,985	1,627	2,105	1,537	1,847	1,255	3,572	2,297
Number of dysentery cases	15	10	17	11	19	12	34	22
Number of diarrhea cases	220	123	221	120	78	52	136	80

Table 2: Monthly number of hospital visits by year

	2006	2007	2008	2009	2010	2011
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Number of new hospital visits	4,550	5,343	5,363	5,805	5,507	3,726
Number of hospital re-visits	2,202	3,228	2,474	2,760	2,784	989
Number of dysentery cases	26	31	21	18	19	14
Number of diarrhea cases	158	187	194	186	151	107

Table 3: Climate variables and district characteristics

VARIABLES	(1) Obs	(2) Mean	(3) SD	(4) Min	(5) Max
Monthly minimum temperature (^{0}C)	796	19.07	0.61	17.80	21.00
Monthly maximum temperature (^{0}C)	796	30.18	1.59	28.00	34.40
Mean monthly temperature (^{0}C)	796	24.65	0.98	23.20	27.70
Average monthly rainfall (mm)	796	115.46	64.60	3.60	310.80
1 if month of insufficient rain	796	0.36	0.48	0.00	1.00
Percent HHs no toilet	796	48.75	27.52	20.00	88.00
Proportion of HHs with unsafe water	796	0.28	0.16	0.02	0.45
Proportion of females no formal education	796	0.19	0.08	0.07	0.34
Distance to Gov't hospital	796	25.96	10.19	14.00	42.50
Proportion sleeping under mosquito net	796	59.43	10.21	37.70	78.00
Proportion of HHs without handwashing facility	796	87.60	9.42	69.70	100.00
Percent children age 5 & below	796	12.59	6.05	0.00	22.50

Table 4: Effect of rainfall and temperature on diarrheal cases: OLS regression

VARIABLES	(1) New Attendance	(2) Re-attendance	(3) Diarrhea Acute	(4) Dysentery
1 if month of insufficient rain	656.0**	199.4*	20.78***	2.120*
	(320.9)	(111.2)	(7.200)	(1.239)
Maximum temperature	20.68	-28.42	2.835	1.167***
	(103.4)	(35.79)	(2.315)	(0.396)
Minimum temperature	-133.8	-207.3**	-4.445	-0.769
	(292.6)	(101.8)	(6.475)	(1.114)
Percent HHs no toilet	23.66***	308.0***	11.57***	0.0156
	(8.323)	(63.47)	(4.101)	(0.0320)
1 if age 5 and below	-2,772***	-670.8***	113.6***	-10.53***
	(284.8)	(98.45)	(6.358)	(1.093)
Distance to Gov't hospital	38.35*	173.8***	8.120***	0.00831
	(21.31)	(29.92)	(1.936)	(0.0813)
Percent children age 5 & below	405.0***	-22.28	0.474	1.210***
	(44.19)	(21.62)	(1.393)	(0.170)
_Iyear_2007	-181.8	405.7**	26.00**	-0.258
	(581.3)	(204.6)	(13.22)	(2.222)
_Iyear_2008	3,791***	4,489***	207.5***	2.143
	(644.3)	(1,033)	(66.53)	(2.451)
_Iyear_2009	4,192***	5,123***	203.8***	-0.959
	(643.4)	(1,069)	(68.90)	(2.468)
_Iyear_2010	6,892***	4,904***	199.4**	7.700**
	(914.8)	(1,205)	(77.61)	(3.498)
_Iyear_2011	3,274***	1,337**	61.18	-0.241
	(689.0)	(642.6)	(41.24)	(2.618)
Constant	-2,248	-6,176	-472.8*	-13.06
	(5,198)	(3,910)	(250.7)	(19.94)
Observations	631	631	631	631
R-squared	0.256	0.565	0.528	0.304

Robust standard errors in parentheses. Asterisks ***, ** and * represent significance at one, five and ten percent level, respectively. District dummies are also controlled in all regressions.

Table 5: Effect of rainfall and temperature on diarrheal cases: Poisson regression

VARIABLES	(1) New Attendance	(2) Re-attendance	(3) Diarrhea Acute	(4) Dysentery
1 if month of insufficient rain	0.122**	0.0883*	0.128***	0.113**
	(0.0568)	(0.0454)	(0.0432)	(0.0527)
Maximum temperature	0.00409	-0.00610	0.0196	0.0603***
	(0.0212)	(0.0149)	(0.0134)	(0.0185)
Minimum temperature	-0.0245	-0.0820**	-0.0316	-0.0391
	(0.0446)	(0.0400)	(0.0317)	(0.0463)
Percent HHs no toilet	0.00527**	0.0645**	0.0294	0.000842
	(0.00267)	(0.0304)	(0.0245)	(0.00145)
1 if age 5 and below	-0.564***	-0.284***	0.724***	-0.505***
	(0.0484)	(0.0395)	(0.0391)	(0.0469)
Distance to Gov't hospital	0.00715	0.0356**	0.0299**	0.00202
	(0.00551)	(0.0141)	(0.0121)	(0.00377)
Percent children age 5 & below	0.0805***	-0.0261***	-0.000337	0.0631***
	(0.00763)	(0.00907)	(0.0112)	(0.00984)
_Iyear_2007	-0.0103	0.0652	0.163*	-0.0651
	(0.109)	(0.0679)	(0.0956)	(0.0940)
_Iyear_2008	0.765***	0.752	0.591	0.159
	(0.164)	(0.472)	(0.372)	(0.120)
_Iyear_2009	0.828***	0.906*	0.529	-0.00784
	(0.107)	(0.490)	(0.379)	(0.117)
_Iyear_2010	1.260***	0.711	0.509	0.397***
	(0.137)	(0.569)	(0.456)	(0.144)
_Iyear_2011	0.624***	-0.413	-0.0675	0.0133
	(0.112)	(0.313)	(0.250)	(0.137)
Constant	6.965***	7.499***	3.157**	1.096
	(0.889)	(1.692)	(1.362)	(0.829)
Observations	631	631	631	631
Pseudo R-squared	0.3444	0.6382	0.5281	0.2508

Standard errors in parentheses. The errors were following a Poisson regression and hence, obtaining robust standard errors was not necessary. Asterisks ***, ** and * represent significance at one, five and ten percent level, respectively. District dummies are also controlled in all regressions.

Table 6: Effect of rainfall and temperature on diarrheal cases: Negative binomial regression

VARIABLES	(1) New Attendance	(3) Re-attendance	(5) Diarrhea Acute	(7) Dysentery
1 if month of insufficient rain	0.124**	0.112**	0.145***	0.0769
	(0.0500)	(0.0455)	(0.0429)	(0.0532)
Maximum temperature	-0.000255	-0.00769	0.0190	0.0535***
	(0.0161)	(0.0145)	(0.0138)	(0.0167)
Minimum temperature	-0.0304	-0.0695*	-0.0309	-0.0207
	(0.0461)	(0.0417)	(0.0395)	(0.0484)
Percent HHs no toilet	0.00576***	0.0559**	0.0327	0.000828
	(0.00133)	(0.0263)	(0.0251)	(0.00143)
1 if age 5 and below	-0.593***	-0.331***	0.722***	-0.528***
	(0.0440)	(0.0401)	(0.0378)	(0.0465)
Distance to Gov't hospital	0.00659**	0.0339***	0.0340***	0.000110
	(0.00322)	(0.0124)	(0.0117)	(0.00342)
Percent children age 5 & below	0.0811***	-0.0248***	0.00545	0.0611***
	(0.00699)	(0.00898)	(0.00817)	(0.00735)
_Iyear_2007	-0.00936	0.192**	0.164**	-0.0547
	(0.0891)	(0.0838)	(0.0748)	(0.0913)
_Iyear_2008	0.694***	0.694	0.644	0.110
	(0.0977)	(0.428)	(0.410)	(0.103)
_Iyear_2009	0.784***	0.883**	0.679	-0.0235
	(0.0998)	(0.444)	(0.425)	(0.105)
_Iyear_2010	1.369***	0.689	0.720	0.401**
	(0.152)	(0.500)	(0.474)	(0.156)
_Iyear_2011	0.570***	-0.386	0.0657	-0.0231
	(0.107)	(0.265)	(0.254)	(0.112)
Constant	7.220***	7.578***	2.779*	1.064
	(0.835)	(1.636)	(1.532)	(0.877)
lnalpha	-1.196***	-1.382***	-1.533***	-1.261***
	(0.0538)	(0.0552)	(0.0567)	(0.0664)
Pseudo R-squared	0.0249	0.0591	0.0665	0.0567
Observations	631	631	635	631

Standard errors in parentheses. The errors were following a Poisson regression and hence, obtaining robust standard errors was not necessary. Asterisks ***, ** and * represent significance at one, five and ten percent level, respectively. District dummies are also controlled in all regressions.